A Viewing-Angle Dependent Split-Window Method for Retrieving Land-Surface Temperatures from Space

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Abstract — We propose a generalized split-window method for retrieving land-surface temperature (LST) from AVHRR data. Accurate radiative transfer simulations show that the coefficients in the split-window algorithm for LST must depend on the viewing angle, if we are to achieve a LST accuracy of about 1 °K for the whole scan swath range (±50.3 ° from nadir) and for the ranges of surface temperature and atmospheric conditions over land, which are much wider than those over oceans. The coefficients in the split-window algorithm also vary with atmospheric column water vapor and boundary temperature. The column water vapor and boundary temperature can be estimated from HIRS/2 data or MODIS atmospheric sounding channels data. We obtain these coefficients from regression analysis of radiative transfer simulations, and we analyze sensitivity and error by using results from systematic radiative transfer simulations over wide ranges of surface temperature and emissivities, and atmospheric water vapor abundance and temperatures. This method is more suitable for retrieving LST from EOS's MODIS data.

INTRODUCTION

Land-surface temperature (LST) is one of the key parameters in the physics of land-surface processes on a regional as well as global scale, combining the results of all surface-atmosphere interactions and energy fluxes between the atmosphere and the ground. Therefore it is required for a wide variety of climatic, hydrological, ecological and biogeochemical studies. In order to understand the entire Earth system better on the global scale, the Earth Observing System (EOS) will provide surface kinetic temperatures at specified accuracies of 0.3 °K for oceans and 1 °K over land.

During the past decade, significant progress has been made in estimation of land-surface temperature from satellite thermal infrared data. The split-window LST method corrects for atmospheric effects based on the differential absorption in adjacent infrared bands [1, 2, 3, 4, 5].

One of the major difficulties in development of LST algorithms is the considerable spectral variation in emissivities for different land-surface materials. Emissivity may also vary with the viewing angle. In laboratory measurements of bare soils, Labed and Stoll [6] showed that this angular effect is smaller at wavelengths 10.6 and 12.0 μm than at 3.7 μm. Oblique viewing results in a shift of the signature, the spectral features being essentially unchanged. At viewing angle 60°, this angular effect does not exceed 1.5% for sand and silty materials but it is about 5% for agricultural soils. In vegetation, the emitted radiation also varies with the viewing angle because of temperature structure in the vegetation canopy. Despite all these variations, spectral emissivity characteristics for terrestrial land covers are relatively stable in the wavelength range 10.5-12.5μm, where AVHRR bands 4 and 5, and MODIS bands 31 and 32 are located. Moreover, spectral contrast in surface emissivities usually decreases with aggregation as spatial scale increases. Salisbury and D'Aria [7] published spectral reflectance data of 79 terrestrial materials including igneous, metamorphic, and sedimentary rocks, varnished rock surfaces, lichen-covered sandstone, soil samples, green foliage, senescent foliage, ice, and water surfaces with suspended quartz sediment and oil slicks. The band average emissivities ε_4 and ε_5 in NOAA-11 AVHRR bands 4 and 5 were calculated from these reflectance spectra. We can gain the following insights into the band average emissivities of terrestrial materials: (1) all ε_4 and ε_5 are larger than 0.825; (2) a general relation $-0.015 \le \varepsilon_5 - \varepsilon_4 \le 0.023$ holds for all samples except fresh rocks, smooth surface of distilled water ice, and senescent beech foliage; (3) ε_4 and ε_5 are larger than 0.91 for all samples except fresh rock and senescent leaves. Salisbury and D'Aria [7] also point out that multiple scattering within the vegetation canopy will reduce spectral contrast and that typical trees, bushes, and grass have emissivities quite close to 1.

A VIEW-ANGLE DEPENDENT LST ALGORITHM

Becker and Li [3] presented a split-window AVHRR LST algorithm for viewing angles up to 46 ° from nadir in form of

$$T_s = A_0 + (1 + P_1 \frac{1-\varepsilon}{\varepsilon} + P_2 \frac{\delta\varepsilon}{\varepsilon^2}) \frac{T_4 + T_5}{2} + (M_1 + M_2 \frac{1-\varepsilon}{\varepsilon} + M_3 \frac{\delta\varepsilon}{\varepsilon^2}) \frac{T_4 - T_5}{2} \qquad (1)$$

where $\varepsilon = 0.5\,(\varepsilon_4 + \varepsilon_5)$, and $\delta\varepsilon = \varepsilon_4 - \varepsilon_5$.

Since the maximum viewing angle for AVHRR sensors is 69 ° from nadir at the Earth surface, pixels with viewing angle larger than 46 ° account for nearly 30% of the total pixels, or almost 50% of the total coverage area within each swath. We have to develop a LST algorithm for the whole viewing angle range in order to provide a global coverage for LST. We developed a view-angle dependent LST algorithm

$$T_s = C + (A_1 + A_2 \frac{1-\varepsilon}{\varepsilon} + A_3 \frac{\Delta\varepsilon}{\varepsilon^2}) \frac{T_4 + T_5}{2} + (B_1 + B_2 \frac{1-\varepsilon}{\varepsilon} + B_3 \frac{\Delta\varepsilon}{\varepsilon^2}) \frac{T_4 - T_5}{2}, \qquad (2)$$

where coefficients C, A_i and B_i depend on viewing angle θ_v. A_1 is not fixed at 1, so there is one more variable coefficient in this form than in Becker-Li [3] algorithm. We have examined the view-angle effect by comparing the accuracies of the θ_v-independent algorithm with the θ_v- dependent

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algorithm. In the θ_v-independent algorithm, coefficients are obtained by regression analysis of simulation data sampled from the whole θ_v range. In the θ_v-dependent algorithm, coefficients are obtained by regression analysis of simulation data at individual viewing angles. The atmospheric lower boundary temperature, i.e., T_{air}, ranges from 256 °K to 287 °K, and atmospheric vertical column water vapor (wv_v) ranges from almost 0 to 2cm. The upper half of Table I is for the first emissivity group with higher band emissivities, and the lower half is for the second emissivity group. The first row in each portion gives RMS and maximum errors in these two methods at viewing angles 69°, 45° and 0°, for algorithms whose coefficients are obtained by regression analysis of data for the whole surface temperature range ±16 °K from T_{air} and the whole wv_v range. Although the θ_v-independent and θ_v-dependent algorithms give almost the same maximum errors, the RMS errors in the θ_v-dependent are smaller at all viewing angles. Since the maximum error is larger than 4 °K even in the θ_v-dependent algorithm, we tried LST iterations once and twice. In the first LST iteration, we used LST coefficients for the two T_s sub-ranges, one from -2 to +16 °K, another from -16 to +2 °K. The retrieved T_s value is used to determine which sub-range should be used in the first iteration. If the surface temperature is within its upper sub-range, both RMS and maximum errors can be significantly reduced. If the surface temperature is within its lower sub-range, no improvement can be made due to the small TIR signature from the surface. If we divide the T_s range into 4 sub-ranges, a second iteration improves the LST accuracy in some sub-ranges. In this way, the θ_v-dependent algorithm improves the LST accuracy by a factor from 1 to 3.

The θ_v-dependent LST algorithm is better than the θ_v-independent algorithms because the optical path at viewing angle 69° is more than twice that in the vertical direction. As atmospheric column water vapor is larger than 4.5cm, the atmospheric transmission function reduces by a factor of 3 from nadir to viewing angle 69° in AVHRR band 4, and by a factor of 4 in AVHRR band 5. The θ_v-dependent algorithm will be the only choice to retrieve LST at an accuracy of the 1 °K level. We can significantly improved the LST accuracy by separating the column water vapor range into 1cm or 0.5cm intervals. The accuracy of the θ_v-independent LST algorithm is only slightly improved by using the column water vapor information, but the accuracy of the θ_v-dependent LST algorithm can be dramatically improved by the information about column water vapor. With one iteration of the 1cm-interval θ_v-dependent algorithm, the RMS error does not exceed 0.7 °K and the maximum error does not exceed 3 °K even at the largest viewing angle. If the LST algorithm for column water vapor intervals of 0.5cm is used, the RMS error does not exceed 0.5 °K and the maximum error does not exceed 1.7 °K at viewing angle 69°. In the viewing angle range up to 45°, the RMS error does not exceed 0.3 °K and the maximum error does not exceed 0.9 °K.

When column water vapor in a tropical atmosphere is greater than 4cm, the atmospheric transmission functions in AVHRR bands 4 and 5 reduce to 0.22 and 0.12, respectively, and LST retrieval from satellite TIR data becomes difficult at large viewing angles. In order to get a quantitative assessment of the retrieved LST accuracy, we developed two sets of θ_v-dependent algorithms for two ranges of the atmospheric lower boundary temperature, one from 300 °K to 310 °K, the other from 300 °K to 305 °K. When column water vapor is less than 4cm, the two sets of LST algorithms have almost the same accuracy. When column water vapor is larger than 4cm, the maximum temperature deficit may be larger than 27 °K. The RMS and maximum error of the LST algorithm for the wider T_{air} range may be larger than 1 °K and 3.8 °K, respectively. The maximum LST error can be reduced by 1-2 °K if the 300-305 °K LST algorithm is used.

SENSITIVITY ANALYSIS

A better LST algorithm must have the following two features: (1) it retrieves LST more accurately; (2) it is insensitive to uncertainties in our knowledge of surface emissivities and atmospheric properties, and to the instrument noise. According to (2), the factors on the emissivity terms $(1-\varepsilon)/\varepsilon$ and $\Delta\varepsilon/(\varepsilon^2)$ are

$$\alpha = A_2 \frac{T_4 + T_5}{2} + B_2 \frac{T_4 - T_5}{2} \tag{3-a}$$

and

$$\beta = A_3 \frac{T_4 + T_5}{2} + B_3 \frac{T_4 - T_5}{2}. \tag{3-b}$$

Simulations show that in cold, dry atmospheric conditions there is no significant difference in maximum α values of the θ_v-independent and θ_v-dependent LST algorithms but the maximum β values are very different. Over the column water vapor sub-range 0.5-1cm, max (β) values in the θ_v-independent LST algorithm are 157 and 147 in the higher and lower emissivity groups, respectively, at the nadir viewing direction. They are larger than twice the values in the θ_v-dependent algorithm. This means that the θ_v-independent algorithm will have a LST error up to 1.6 °K if there is an uncertainty of 0.01 in the value of $\Delta\varepsilon/(\varepsilon^2)$. We expect that this uncertainty is around 0.005 for well known land surfaces such as dense vegetation, snow and ice, and lakes. The θ_v-independent algorithm will have a 0.8 °K error. The θ_v-dependent algorithm is much less sensitive to the value $\Delta\varepsilon/(\varepsilon^2)$, giving a maximum LST error around 0.37 °K in the nadir viewing direction. In warm atmospheric conditions, 294 °K $\le T_{air} \le$ 300 °K, the maximum β value in the θ_v-independent algorithm is as large as 181, its corresponding value in θ_v-dependent algorithm is 92. As expected, all LST algorithms are more sensitive to the uncertainty in $\Delta\varepsilon$ in dry atmospheric conditions. This sensitivity decreases as atmospheric column water vapor is larger, because of the compensative effect of the reflected downward atmospheric thermal infrared radiation.

In order to investigate the sensitivity of the θ_v-dependent LST algorithm to instrument noise, we simulate the instrument noise by synthetic quantization. The radiance values of AVHRR bands 4 and 5 saturate at about 325 °K. The radiance values are expressed by a 10-bit integer through synthetic quantization and then converted to double precision floating point number by multiplying the quantization step.

We compare the RMS and maximum LST errors by apply the same θ_v-dependent algorithm to the original simulation data and the data after synthetic quantization. We change 10 bits to 9 bits and make a similar comparison. The RMS and maximum error due to quantizations using 9 bits are 0.2 °K and 0.7 °K. They are 0.1 °K and 0.4 °K, respectively, for all viewing angles up to 69° if 10 bits are used in the quantization. These results show that the θ_v-dependent LST algorithm is quite stable with 10-bit AVHRR data. It is even more stable with 12-bit MODIS data.

CONCLUSION

We propose a view-angle dependent split-window method for retrieving land-surface temperature from AVHRR and MODIS data. The atmospheric column water vapor and lower boundary temperature values retrieved from HIRS/2 or MODIS atmospheric sounding channels can be used to significantly increase the accuracy of this LST method. This θ_v-dependent algorithm not only retrieves LST more accurately but is also less sensitive than θ_v-independent LST algorithms to the uncertainty in surface band emissivities and to the instrument noise.

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REFERENCES

[1] J. C. Price, "Land surface temperature measurements from the split window channels of the NOAA-7 AVHRR," *J. Geophys. Res.*, vol. 79, pp. 5039-5044, 1984.

[2] Z. Wan and J. Dozier, "Land-surface temperature measurement from space: physical principles and inverse modeling," *IEEE Trans. Geosci. Remote Sens.*, vol. 27, no. 3, pp. 268-278, 1989.

[3] F. Becker and Z. L. Li, "Toward a local split window method over land surface," *Int. J. Remote Sens.*, vol. 3, pp. 369-393, 1990.

[4] A. Vidal, "Atmospheric and emissivity correction of land surface temperature measured from satellite using ground measurements or satellite data," *Int. J. Remote Sens.*, vol. 12, no. 12, pp. 2449-2460, 1991.

[5] Y. H. Kerr, J. P. Lagouarde, and J. Imbernon, "Accurate land surface temperature retrieval from AVHRR data with use of an improved split window algorithm," *Remote Sens. Environ.*, vol. 41, no. 2-3, pp. 197-209, 1992.

[6] J. Labed and M. P. Stoll, "Angular variation of land surface spectral emissivity in the thermal infrared: laboratory investigations on bare soils," *Int. J. Remote Sens.*, vol. 12, no. 11, pp. 2299-2310, 1991.

[7] J. W. Salisbury and D. M. D'Aria, "Emissivity of terrestrial materials in the 8-14 μm atmospheric window," *Remote Sens. Environ.*, vol. 42, pp. 83-106, 1992.

Table I. Comparison between θ_V-independent and θ_V-dependent split-window LST algorithms: RMS (max) errors in range of $T_{air} \le 287.2$ °K and $wv_V < 2$cm.

ranges wv_V	T_s-T_{air}	θ_V-independent 69°	45°	0°	θ_V-dependent 69°	45°	0°
		($0.96 \le \varepsilon_5 \le 1.0$ and $-0.025 \le \varepsilon_4-\varepsilon_5 \le 0.015$)					
0-2	A	1.0 (4.5)	0.4 (2.5)	0.5 (2.0)	0.6 (4.2)	0.4 (2.5)	0.3 (2.1)
0-2	B	1.1 (2.3)	0.4 (1.8)	0.6 (1.7)	0.3 (2.2)	0.2 (1.4)	0.2 (1.2)
0-2	C	0.9 (4.3)	0.4 (2.3)	0.4 (1.8)	0.7 (4.1)	0.4 (2.4)	0.3 (1.9)
0-1	A	0.8 (1.9)	0.2 (1.0)	0.4 (1.2)	0.6 (1.7)	0.2 (0.9)	0.1 (0.8)
0-1	B	1.0 (1.8)	0.3 (0.8)	0.5 (1.1)	0.1 (0.8)	0.1 (0.5)	0.1 (0.5)
0-1	C	0.6 (1.3)	0.2 (0.8)	0.3 (0.8)	0.2 (1.2)	0.1 (0.8)	0.1 (0.7)
0-0.5	A	0.8 (1.6)	0.2 (0.7)	0.4 (1.1)	0.1 (0.6)	0.1 (0.5)	0.1 (0.5)
0-0.5	B	1.0 (1.5)	0.2 (0.5)	0.5 (1.0)	0.1 (0.4)	0.1 (0.4)	0.1 (0.4)
0-0.5	C	0.6 (1.0)	0.1 (0.4)	0.3 (0.7)	0.1 (0.4)	0.1 (0.3)	0.1 (0.3)
0.5-1	A	0.8 (1.9)	0.3 (0.7)	0.4 (1.1)	0.2 (1.0)	0.1 (0.7)	0.1 (0.6)
0.5-1	B	0.9 (1.8)	0.3 (0.8)	0.5 (1.1)	0.1 (0.6)	0.1 (0.4)	0.1 (0.4)
0.5-1	C	0.5 (1.2)	0.2 (0.5)	0.3 (0.7)	0.2 (0.8)	0.1 (0.6)	0.1 (0.5)
1-2	A	0.9 (3.6)	0.4 (1.5)	0.5 (1.2)	0.5 (2.7)	0.3 (1.5)	0.2 (1.3)
1-2	B	0.8 (2.0)	0.4 (1.5)	0.5 (1.3)	0.3 (1.6)	0.2 (1.0)	0.2 (0.8)
1-2	C	0.7 (3.4)	0.3 (1.4)	0.3 (1.0)	0.6 (2.7)	0.3 (1.5)	0.2 (1.2)
1-1.5	A	0.7 (1.8)	0.3 (0.9)	0.4 (1.0)	0.3 (1.2)	0.2 (0.8)	0.1 (0.7)
1-1.5	B	0.7 (1.5)	0.4 (0.9)	0.4 (1.1)	0.2 (0.8)	0.1 (0.5)	0.1 (0.4)
1-1.5	C	0.5 (1.7)	0.2 (0.6)	0.3 (0.7)	0.3 (1.1)	0.2 (0.7)	0.1 (0.6)
1.5-2	A	0.8 (2.9)	0.4 (0.9)	0.4 (1.1)	0.4 (1.6)	0.2 (0.9)	0.2 (0.7)
1.5-2	B	0.7 (1.7)	0.4 (1.1)	0.4 (1.2)	0.2 (1.0)	0.1 (0.6)	0.1 (0.5)
1.5-2	C	0.7 (2.8)	0.3 (0.7)	0.3 (0.9)	0.4 (1.5)	0.2 (0.8)	0.2 (0.7)
		($0.91 \le \varepsilon_5 \le 0.95$ and $-0.025 \le \varepsilon_4-\varepsilon_5 \le 0.015$)					
0-2	A	1.0 (5.1)	0.5 (2.8)	0.5 (2.1)	0.7 (4.8)	0.4 (2.9)	0.4 (2.4)
0-2	B	1.0 (2.6)	0.4 (2.2)	0.6 (2.0)	0.4 (2.8)	0.3 (1.8)	0.2 (1.6)
0-2	C	0.9 (4.8)	0.5 (2.4)	0.4 (1.7)	0.9 (4.5)	0.5 (2.4)	0.4 (2.0)
0-1	A	0.8 (1.9)	0.2 (1.0)	0.4 (1.2)	0.2 (1.5)	0.2 (1.1)	0.2 (1.0)
0-1	B	1.0 (1.8)	0.3 (0.9)	0.5 (1.1)	0.2 (0.9)	0.1 (0.6)	0.1 (0.6)
0-1	C	0.5 (1.5)	0.2 (0.8)	0.3 (0.8)	0.2 (1.2)	0.2 (0.9)	0.1 (0.8)
0-0.5	A	0.8 (1.6)	0.2 (0.8)	0.4 (1.2)	0.1 (0.7)	0.1 (0.6)	0.1 (0.6)
0-0.5	B	1.0 (1.5)	0.2 (0.6)	0.5 (1.0)	0.1 (0.5)	0.1 (0.4)	0.1 (0.4)
0-0.5	C	0.5 (1.0)	0.1 (0.5)	0.3 (0.9)	0.1 (0.5)	0.1 (0.4)	0.1 (0.4)
0.5-1	A	0.7 (1.9)	0.3 (0.7)	0.4 (1.1)	0.2 (1.0)	0.2 (0.8)	0.1 (0.7)
0.5-1	B	0.9 (1.7)	0.3 (0.7)	0.5 (1.0)	0.1 (0.7)	0.1 (0.5)	0.1 (0.4)
0.5-1	C	0.5 (1.2)	0.2 (0.6)	0.3 (0.7)	0.2 (0.8)	0.1 (0.6)	0.1 (0.6)
1-2	A	0.9 (4.0)	0.4 (1.6)	0.5 (1.3)	0.6 (3.1)	0.3 (1.8)	0.3 (1.5)
1-2	B	0.8 (2.4)	0.4 (1.6)	0.5 (1.3)	0.3 (1.9)	0.2 (1.2)	0.2 (1.0)
1-2	C	0.8 (3.9)	0.4 (1.5)	0.4 (1.2)	0.7 (2.9)	0.4 (1.6)	0.3 (1.3)
1-1.5	A	0.7 (2.0)	0.3 (1.0)	0.4 (1.1)	0.3 (1.3)	0.2 (0.9)	0.2 (0.8)
1-1.5	B	0.7 (1.5)	0.3 (0.9)	0.4 (1.1)	0.2 (0.9)	0.1 (0.6)	0.1 (0.5)
1-1.5	C	0.5 (1.9)	0.2 (0.7)	0.3 (0.7)	0.3 (1.1)	0.2 (0.8)	0.2 (0.7)
1.5-2	A	0.8 (3.3)	0.4 (1.0)	0.4 (1.2)	0.4 (1.8)	0.3 (1.0)	0.2 (0.9)
1.5-2	B	0.7 (2.1)	0.4 (1.0)	0.4 (1.2)	0.3 (1.2)	0.2 (0.7)	0.1 (0.6)
1.5-2	C	0.8 (3.2)	0.3 (0.9)	0.4 (1.1)	0.5 (1.7)	0.3 (0.9)	0.2 (0.8)

A: -16 to 16 °K; B: -2 to 16 °K; C: -16 to 2 °K.